Demand Control Ventilation based on Bayesian Estimation of Occupancy

by Haolia Rahman

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Abstract: This paper investigates methods for estimating indoor occupants using Bayesian method based on carbon dioxide concentrations for demand control ventilation applications. The estimation algorithm has been tested in an office room and sources of errors have been investigated including physical and computational time delays in estimation. Experiments have been conducted to control the outdoor airflow rate in real-time according to the estimated number of occupants. Occupant-based ventilation schemes show low airflow rates compared to other ventilation schemes, while maintaining carbon dioxide level within 1000 ppm.

Keywords: Occupancy estimation, Bayesian method, Carbon dioxide concentration, Demand control ventilation.

1. Introduction

Ventilation is essential to maintain comfortable and healthy indoor environments. It is important to supply fresh outdoor air in energy-efficient ways. The amount of energy for HVAC by commercial buildings in Korea is reported to be approximately 49% of their total energy consumption[1]. As buildings become airtight and well-insulated to reduce energy consumptions, the percentage of ventilation energy increases relatively. Because the minimum outdoor fresh air needs to be supplied and cannot be reduced further.

Extensive research and development have been conducted to achieve efficient ventilation in smart ways. Smart ventilation strategy includes smart hardware, smart room airflow design, smart use of cool outdoor air, and smart control and operation. Smart hardware includes efficient fans, low-pressure duct components, and heat recovery ventilators. Smart room airflow means improved ventilation effectiveness for a given airflow rate. Various room air movements have been designed such as displacement ventilation and personal ventilation, and etc. Smart use of outdoor air includes outdoor air cooling and night purging to take advantage of outdoor conditions. Natural ventilation is another way of reducing ventilation energy for mechanical fans. Finally, smart control and operation is the demand-controlled ventilation to change airflow rates according to the demand of occupants. There are time-based, concentration-based, and occupancy-based DCV schemes.

Occupant information is needed for occupancy-based DCV. Occupants can be monitored either by direct sensors such as passive infrared (PIR) sensors[2], radio-frequency identification (RFID) tags[3], and video cameras, or by indirect measurements of environmental conditions such as CO_2 concentrations, sound levels, humidity, and temperature. Depending on monitoring sensors, various types of information can be obtained, from more presence, number counts, locations, activity levels, distributions, and even trajectories or identifications of occupants. Indirect sensing methods are preferred over direct monitoring, which can hinder privacy. Among the aforementioned indirect methods, CO_2 concentration measurements show the strongest correlation with occupancy rates[4].

An artificial neural network (ANN) has been frequently used, which is a statistical modeling tool for investigating complex nonlinear relationships between input and output variables. Therefore, research on predicting population of indoor occupants using ANN method are exensively used [5] Bayesian model can be used to determine the number of occupants by a probabilistic approach[2, 6]. Shin et al.[7] applied a Bayesian method to estimate the number of people in a subway station on the basis of measured CO_2 concentrations. Wei et al. [8] used a frequentist maximum likelihood algorithm and Bayesian estimation for electric energy prediction.

It is the objective of the present paper to develop an occupancy estimation method using Bayesian Markov chain Monte Carlo algorithm based on indoor CO_2 concentration data, and to apply it to control ventilation rates in an office on a real time basis.

2. Bayesian MCMC Method

According to Bayes' theorem, the posterior probability $\pi(\theta|x)$ is computed on the basis of the prior probability $\pi(\theta)$ and the likelihood function $f(x|\theta)$ as follows:

$$\pi(\theta|x) = \frac{\pi(\theta)f(x|\theta)}{\int \pi(\theta)f(x|\theta)d\theta} \quad (1)$$

Here, θ is an occupancy level based on the observed CO_2 concentration x. We input the prior information based on the most likely occurrences in the observed system, and this approach should approximate the actual values as closely as possible. Four priors are set according to our system, with N prior determining the probability of the occupancy level and the three remaining priors ($\dot{m}$, C_{out}, Q) determining the CO_2 concentration as shown in Fig. 1.

The Markov chain Monte Carlo (MCMC) approach generates random sampling from some probability distribution so that Bayes' process can be applied repeatedly. Finally, we use the Metropolis–Hastings (MH) algorithm, which rejects or accepts the sample trials of some proposed moves. A detailed description of the Bayesian MH-MCMC algorithm can be found in Rahman and Han[9].

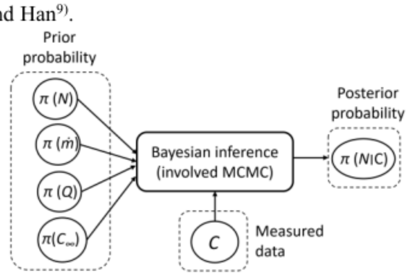


Fig. 1 Procedure for Bayesian inference of occupancy

3. Experimental Setup

Experiments were conducted in a laboratory office located in the engineering building of Kookmin University. The floor area and volume of the room are approximately 37.2 m^2 and 96.7 m^3 respectively. The space can accommodate six students. As can be seen in Fig. 2, air ducts are installed above ceiling panels, and the supply and return grills are placed at opposite corners of the room. Carbon dioxide sensors and airflow sensors are installed in the supply and return ducts. The CO_2 sensors have been calibrated using two standardized gases (500 ppm and 2000 ppm) with the accuracy of the sensor of ±3% in the range 0-5000 ppm. Another CO_2 sensor is installed in the middle of the room at the height of 2 m. Two laser beams installed between door frames to detect the direction of movement indicated by breaks of the beams as people walk by. This counter provides reliable number counts and directions, from which actual number of occupants are obtained.

All the sensor outputs were acquired at one-minute interval by DAQ. LabView was used to collect the data, execute the occupancy estimation algorithm, and control the ventilation rate.

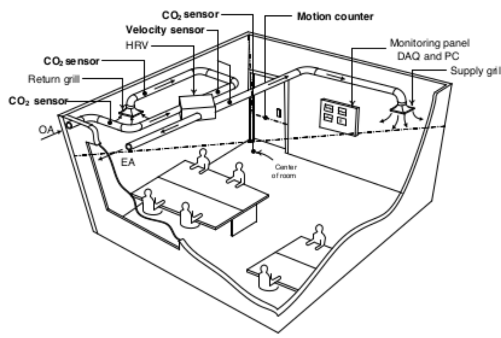


Fig. 2 Experimental test room

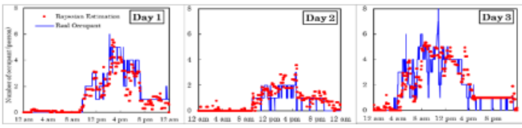
4. Results and Discussion

Results are shown in Fig. 3 in comparison with actual occupancy for constant and varying airflow rate cases. The error of the estimated number of occupants is expressed by the coefficient of variance.

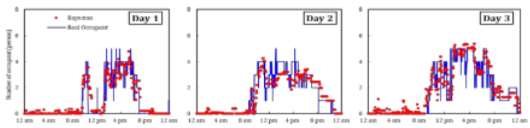
$$CV = \sqrt{\frac{\Sigma(N_{est}-N_{act})^2}{n-1}} / \bar{N}_{act} \ , \quad (1)$$

where N_{est} and N_{act} are estimated and actual numbers of occupants, and n is the number of data points. The over bar means the average.

Agreements are not perfect but are quite reasonable. The CV for constant airflow rate is 34.6%, which is slightly lower than that for varying flow rate at 39.8%.



(a) Constant airflow rates



(b) Varying airflow rates

Fig. 3 Comparison of estimated and actual occupancy

The discrepancies are caused by the statistical uncertainties of prior variables as well as the time delays in estimating occupancies.

In order to investigate the time delay in estimating N, the correlation coefficients are calculated. They indicate the coincidence of two functions with respect to the time shift of T.

$$R^2(T) = \frac{\int N_{est}(t) \cdot N_{act}(t-T)\, dt}{\int N_{est}(t) \cdot N_{act}(t) dt} \qquad (2)$$

Figure 4 shows the results for 6 different ventilation cases, each of which consists of 3 days. It is interesting to notice the maximum correlation coefficients occur at 20-25 minutes for all cases.

The time delays are generated by the physical responses of the system and the computational time for Bayesian statistics as shown in Fig. 5. After a person enters the room, it takes time for the generated CO_2 to disperse into the room. The dispersion time depends on the size or the time constant of the room. The sensor response time depends on sensor specifications, which is approximately 1 min for the present CO_2 sensors. In addition, several time steps are required in order to monitor dynamic changes. After acquiring data, computation time is required for data processing such as iteration and averaging, which is not quite considerable. Fans are usually controlled not too frequently but with appropriate time intervals, but it is controlled at every minute for the present experiment.

The time delay of 20-25 min includes all the time durations required for the processes described above.

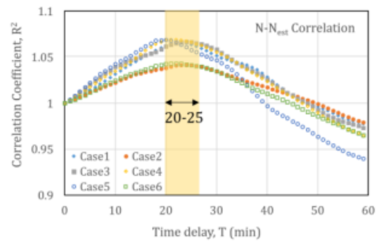


Fig. 4 Time delay in estimating number of occupants

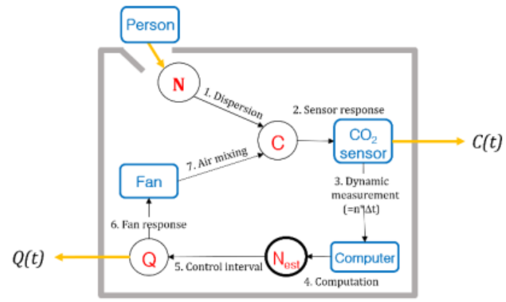
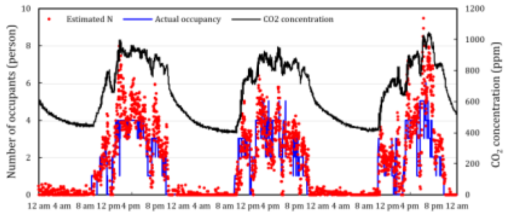


Fig. 5 Time delay in real-time ventilation control

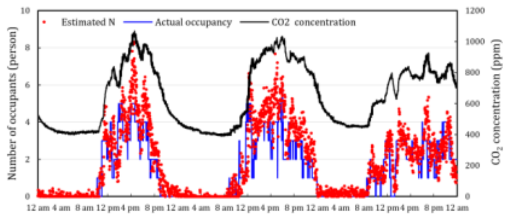
Next step is to control ventilation rates using estimated occupancy information on a real-time basis. Various ventilation schemes were tested, such as time-based, concentration-based, and occupancy-based schemes. Results of two occupancy-based ventilation schemes are shown. Fig. 6(a) shows the results when the airflow rate is directly proportional to the estimated number of occupants, and Fig. 6(b) shows the results when the airflow rate is determined by the occupancy and the floor area according to ASHRAE standard 62.1[10].

Indoor CO_2 concentrations are maintained below 1000 ppm for both cases, and average concentrations are nearly the same. Ventilation rate is greater by 14% for ASHRAE scheme, since minimum ventilation rate is maintained when the room is vacant. ASHRAE scheme is suggested because of possible unknown indoor contaminants other than CO_2 which can be generated from building materials and other sources.

A summary of results is shown in Table 1. T-control sets the ventilation rate constant during office hours, and Q-control set the ventilation rate proportional to indoor CO_2 concentrations. Average ventilation rates per person are relatively low for occupant-based schemes compared to T-control and C-control schemes, while CO_2 levels are comparable.



(a) Directly proportional to occupancy



(b) Proportional to occupancy plus a fixed minimum

Fig. 6 Real-time control of airflow rate based on estimated number of occupants

Table 1. Summary of ventilation control results

	Control schemes			
	T-control	Q-control	N-control	ASHARE
Average N	2.75	2.23	2.66	2.64
Average CO_2 (ppm)	762	689	798	800
Total supply air volume (m^3/day)	1440	1721	718	939
Average Q (L/s)	39.5	30.3	17.4	20.3
Average Q per person (L/s person)	14.4	13.6	6.5	7.7

It shows the Bayesian method is applicable not only to occupancy estimation but also to control the ventilation rate based on the estimated number of occupants. It does not cause any recursive problems in feedback control. Even though the algorithm adopts informative priors, with the proposed method, a false estimation at the current step would not significantly affect the calculation of the next step.

6. Conclusions

The real-time ventilation control based on the estimated occupancy by Bayesian works successful without causing any recursive problems.

According to the experimental results of various ventilation schemes, occupant-based DCV (ASHRAE) is most effective compared to other schemes in terms of indoor environmental quality and the total ventilation air volume.

The estimation method and control algorithm should be further improved to reduce the errors and time delays and to make more robust and durable for real applications of DCV.

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